Exploratory Spatial-Temporal Visualization of Hurricane Impacts on Crime Events in Miami, Florida

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Abstract: Natural disaster research has illuminated the complex natural and social processes that occur after a natural disaster. Despite emergent efforts given to understanding the relationship between natural disasters and crime, few geographers have studied the effect that natural disasters have on the space-time behavior of crime patterns using local level data (Hagenauer, Helbich, and Leitner 2011; Leitner and Helbich 2011). This study explores, spatially analyzes and geovisualizes spatio-temporal events for better standing in the discovery and identification of events and their emergence. We focus on the task of identifying emerging spatio-temporal crime clusters in event occurrences. We demonstrate the existing techniques and approaches to event exploration (point density, kernel density estimation, scan statistics and 3D geovisualization).

Keywords: Spatial-Temporal Visualization, kernel density estimation, scan statistics and 3D geovisualization, Hurricane, Crime and Event Detection

1. Introduction

Natural disasters and severe weather phenomena are remarkable, yet terrifying displays of power, capable of producing widespread destruction and loss of life. According to the National Hurricane Center (2011), Hurricane Wilma was the fourth costliest and twelfth most intense tropical cyclone since 1975. Despite society's technological advancements, events like Hurricanes Ivan and Wilma demonstrate its inability to forecast chaos, specifically that of crime and deviance. However, hurricanes present "unique laboratories" for researchers to investigate the loss of social controls and patterns of criminal activity (Cromwell et al. 1995). Despite emergent efforts given to understanding the relationship between natural disasters and crime, few geographers have studied the effect that natural disasters have on the space-time behavior of crime patterns using

local level data (Hagenauer, Helbich, and Leitner 2011; Leitner and Helbich 2011). This study seeks to explore, spatially analyze and geovisualize spatio-temporal events for better standing in the discovery and identification of crime events and their cluster emergence.

The ultimate question in this study is "what ways are spatial and temporal distributions of different types of crime altered prior to and following a hurricane disaster event?". In order to answer this question, we demonstrate the existing techniques and approaches to event exploration (point, kernel density estimation, dual kernel density estimation, scan statistics and 3D mapping) before and after Hurricane event.

Until recent years, there has been a limited amount of empirical research which investigates the relationship between disasters and crime. Conflicting findings give no conclusive insight into the reactions of criminal activity following a natural disaster. Researchers have found increased crime rates (Thornton and Voigt 2007; VanLandingham 2007, 2008), decreased crime rates (Suar and Kar 2005), varying rates among different types of crime (Bailey 2009; Zahran 2009; Varano 2010), and unchanged crime rates (Cromwell et al. 1995; Bass 2008) in the wake of a disaster. However, it is generally accepted that crime decreases immediately following a disaster, apart from domestic violence (Enarson 1999) and fraud (Davila, Marquart, and Mullings 2005).

2. Visualization of Crime Clusters for Ecology of Crime

We explore the existing techniques to event exploration including point, kernel density estimation, dual kernel density estimation, scan statistics and 3D geovisualization. The most common approach for displaying geographic patterns of crime is point mapping. The basic of crime mapping starts with geocoded points from raw crime report data. Each point data are suitably attributed with information, such as crime type, data and time of offense. However trying to interpret spatial patterns and hot spots with point maps can be difficult especially when you deal with big data.

Kernel density estimates (KDE) are widely accepted techniques for estimating a surface density from crime point data, as they can easily illustrate density or clustering among points (Fotheringham, Brunsdon, and Charlton 2000; Eck et al. 2005; Chainey and Ratcliffe 2005). When applied to one variable, the previous method is considered a single density estimate. If applied to two variables, the method is called a dual density estimate. The realm of crime analysis has utilized the dual KDE for investigating crime related to other variables with varied results (Oberwittler and Wiensenhütter 2004; Pezzuchi 2004; Leitner and Helbich 2011)..

The space-time scan statistic utilizes numerous overlapping cylindrical scanning windows as potential clusters. The circular base of the cylinder represents the geographic dimension, and the height represents the temporal extent of a possible cluster. The circular window iterates over each crime location, gradually increasing the circle radius and cylinder height to a user-defined maximum value. In this fashion, all cylinder sizes and shapes are considered. Many studies (Jobst, 2007; Kraak, 2002; Meng, 2002; Wolff et al, 2009) highlighted that 3D geovisualization promotes visual thinking about spatial pattern, spatial relationships and trends and it facilitate an intuitive understanding of complex spatial pattern in crime. Undoubtedly, crime volume data even require the third dimension for expressive data visualization in crime

mapping. Recently, Nakaya and Yano discussed the possibility of utilizing space-time cubes in the study of crime, as a means of "visually displaying and comprehending the temporal duration as well as the spatial extent of different crime clusters rather than focusing on an individual cluster" (Nakaya & Yano, 2010, 225). Crime studies can benefit greatly from time sensitive study of data.

3. Case Study: Hurricane Wilma in Miami, Florida

Hurricane Wilma struck south Florida on October 24, 2005, as a category 3 hurricane, before producing ten tornadoes over the peninsula (Figure 1). Wilma is attributed with five directly related deaths and a substantial amount of downed trees, and damaged houses. Wilma also caused the largest disruption of electrical service damage to ever occur in Florida. The extent of this disruption includes outages in 42 Florida counties equal to 98 percent of South Florida. Insurance claims for Wilma totaled $10.3 billion for an estimated $20.6 billion in total damages (National Hurricane Center 2006).

The study area comprises 345 contiguous U.S. Census Bureau block groups in Miami-Dade County (2010), an area of approximately 741 km. Crime data (Burglary, Larceny-theft and Motor Vehicle Theft) were collected for a study period three months prior to and after Hurricane Wilma. This includes the dates 23 July 2005 – 24 January 2006. Types of crime in the datasets were converted to Uniform Crime Reporting (UCR) classifications.

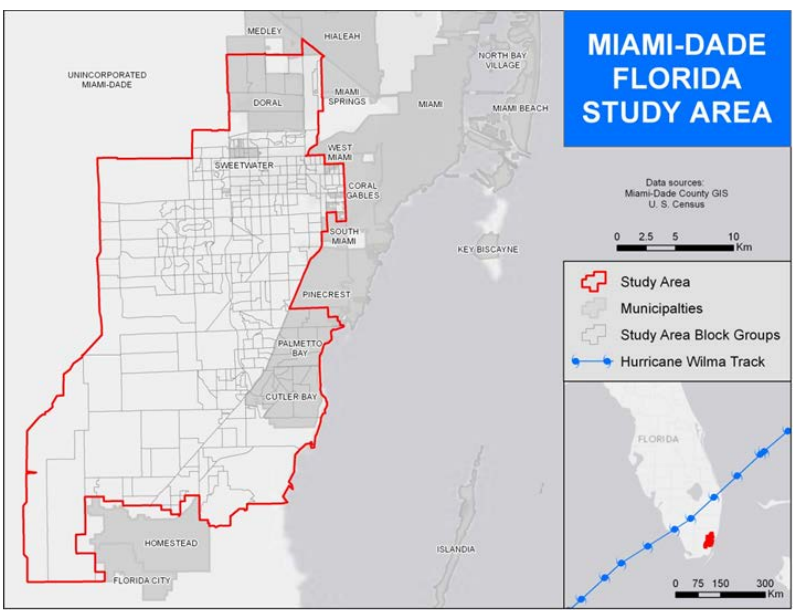

Figure 1. Study Site of Miami-Dade, Florida. A hurricane track for Wilma has been included for reference

4. Visualization Results

4.1 Point Mapping

Figure 2. Spatial distribution of selected crimes across the Miami.

The spatial distribution of burglary and larceny-theft during the study periods appear to be heterogeneously distributed and at higher densities in certain areas. In Miami, these dense areas of crime appear to be located toward the northeast and along the coast.

4.2 Surface - KDE

In this study, we separated our temporal data into 10 day bins; since our study contained 186 total days, this gave us 19 bins, 18 of which each contain 10 days, with the 19th bin containing only data for the final 6 days. After binning the data, we conducted kernel density estimation. After this process was complete, we examined the data and then instituted a common method of symbology between the 19 different bins. An examination of the resulting KDE maps demonstrates the persistence of some hotspots (highlighted with ovals in Figure 3), and the inconsistency of others (highlighted with triangles in Figure 3).

A dual kernel density estimate was calculated for each crime type in which a space time cluster emerged from the scan statistic analysis. For this a “typical” period, or a period with average daily crime totals, was subtracted from a “high” period, or a period representing highest daily crime totals. Miami experience increased burglary in a small pocket to the south, larceny-theft in small pockets to the north and south and theft of morto-vehicle over a relatively larger area to the north (Figure 4).

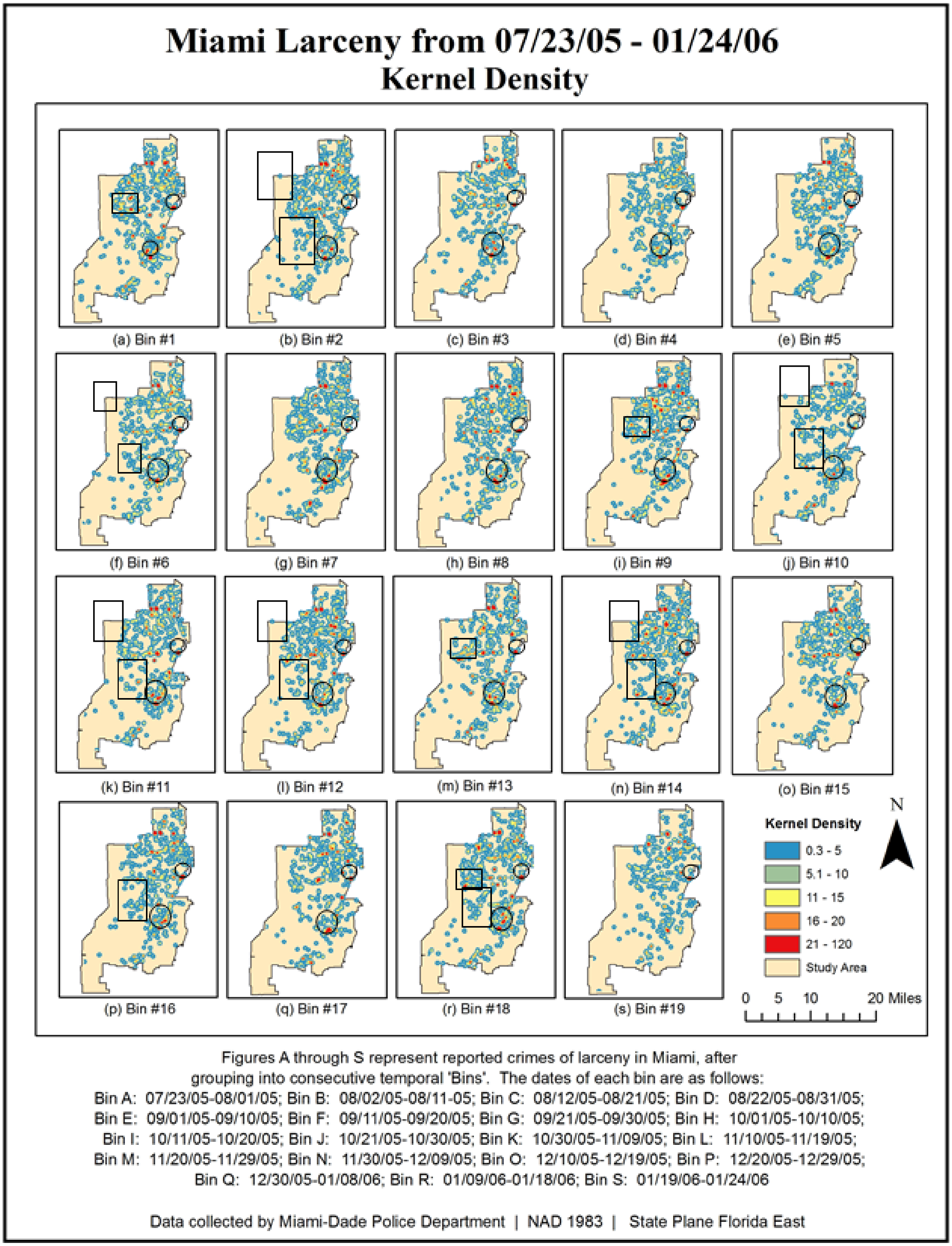

Figure 3. A Series of KDE of Larceny across the Miami.

4.3 Emerging Crime Cluster

The spatial distribution of the space-time clusters reveals generally unique patterns for each crime type (Figure 4). Burglary clusters in Miami are generally located in a small pocket in the north and another in the south, whereas larceny-theft clusters range from large to small clusters and span from the north to the center of the study area. A single theft of motor vehicle cluster is located in the northeast. These clusters demonstrate that crime type influences the location of cluster formation, and that cluster locations vary across space for different types of crime. The clusters also reveal that clusters do not necessarily emerge near areas known for that specific type of crime or areas known for high crime rates in general. For example, larceny-theft clusters 2 and 3 are on the outskirts of established crime, while clusters 4 – 7 are in areas with densely distributed larceny-thefts.

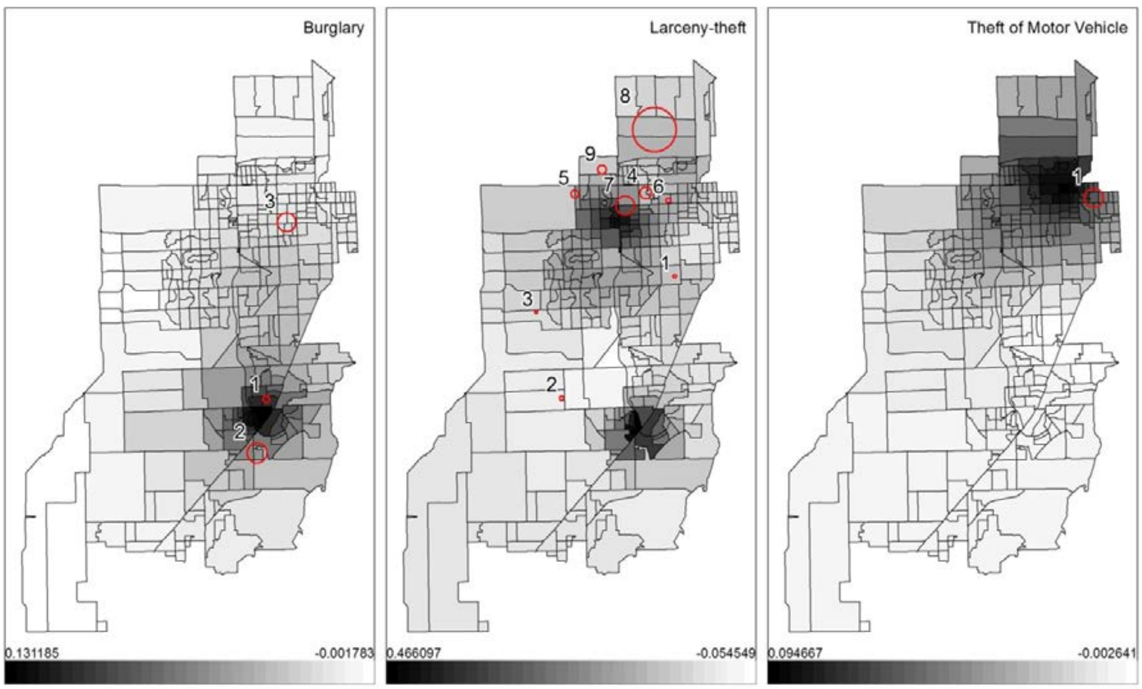

Figure 10. Space-time clusters of crime types (numbers) and crime density (The ranges of values (+/-), as noted at the bottom of each map, represent the change (increase/decrease) of crimes per unit area)

The space-time clusters cluster locations (Figure 4) identified by the scan statistic, when compared to dual kernel density estimates, show some overlap. Clusters 1 and 2 identified by SaTScan coincide with Burglary increased density areas, Cluster 7 of larceny-theft with increased density areas, and Cluster 1 of theft of motor vehicle with increased density areas. The pocket of high larceny-theft densities in the south does not overlap any scan statistic clusters. However, this pocket does coincide with the burglary pocket. In general, a spatio-temporal cluster identified by the scan statistic coincided with each crime density surface,

4.4 3D Geovisualization

3D display of the total crime counts during the study periods (Figure 5) provided an alternative representation of 2D kernel density surface. This allows for visual

differentiation of regions with higher crime density from regions with lower densities of different crime types. The spatial patterns coincide with 2D surface.

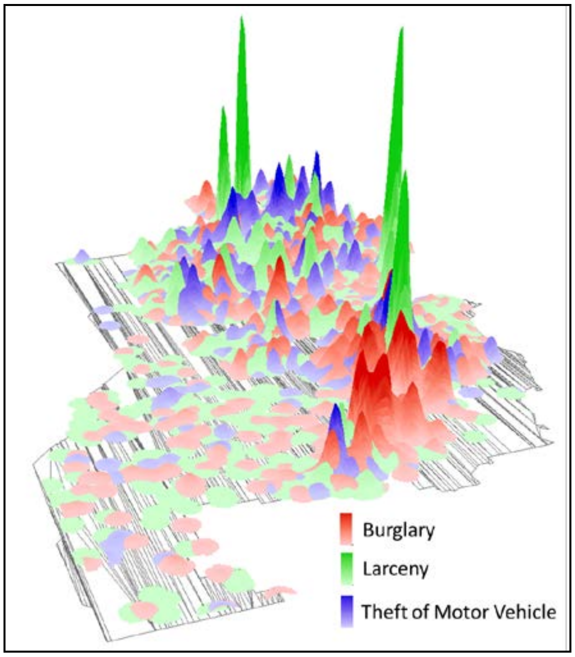

Figure 5. 3D display of crime events (as a total of the study period)

4.5 Temporally-Orientated 3D Geovisualization

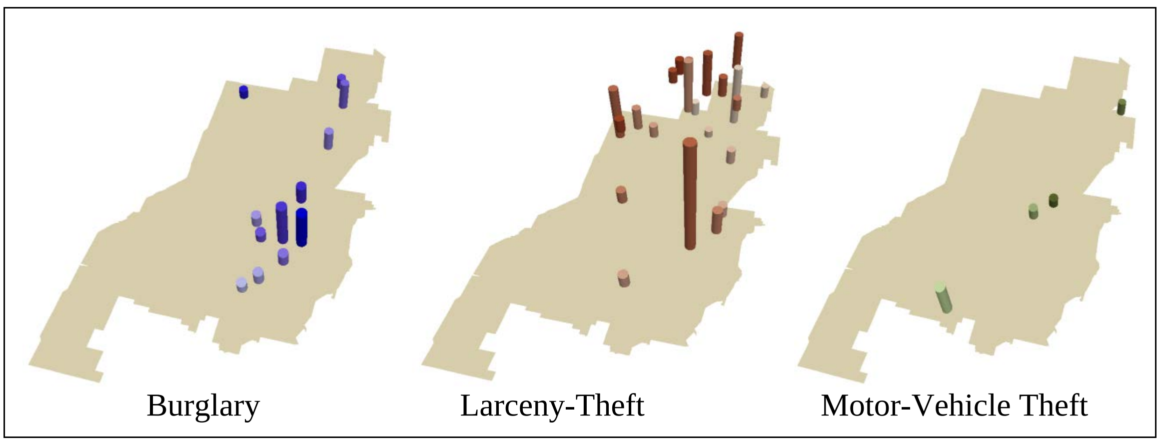

Figure 6. Space-time display of significant high-density clusters detected by space-time scan statistics at vertical view

Figure 6 shows the significant clusters obtained by the scan statistics in the space-time cube. The two aspects of spatio-temporal clusters shown– the stable pillar and the fluid floating island clusters – can be clearly identified. The constant high crime clusters are located around Southeast corner. The spatial distribution of the space-time cluster change show that burglary cluster emerged in the south corner during the hurricane event and larceny-theft clusters and motor-vehicle theft clusters emerging in the south corner and northern corner two months after hurricane.

5. Findings and discussion

Results were similar to previous disaster research, and significant spatio-temporal clusters were identified for burglary, larceny-theft, and theft of motor vehicle. These clusters generally coincided with the nearby landfall of a tropical storm, but not every storm produced crime clusters. Societal structures also influence criminal opportunity and activity, such as orders for mandatory (or voluntary) evacuations or curfews. This paper demonstrated the existing techniques and approaches to event exploration (point density, kernel density estimation, scan statistics and 3D geovisualization) for identifying emerging spatio-temporal crime clusters in hurricane event occurrences in Miami, Florida. As a first step, we created point maps, calculated statistical surfaces based on kernel density estimation techniques and space-temporal cluster based on scan statistics. Afterwards we were able to represent emerging hotspots of the different crime types by various 3d visualization techniques.The spatial distribution of the space-time cluster change revealed the more detailed movement of the clusters over time. 3D geovisualization is useful particularly showing spatial changes through time and can be more effective than 2D visualization. However, the further analysis on the context information particular underlying population and neighborhood characteristics need to be considered. Also further cartographical design techniques will have to be developed to represent three-dimensional time-sensitive spatial data in a more appealing way.

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